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Impact of Range Anxiety on Driver Route Choices using a Panel-Integrated Choice Latent Variable Model

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Impact of Range Anxiety on Driver Route Choices using a Panel-Integrated Choice Latent Variable Model

by

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Abstract

Impact of Range Anxiety on Driver Route Choices using a Panel-Integrated Choice Latent Variable Model

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There has been a significant increase in private vehicle ownership in the last decade leading to substantial increase in air pollution, depleting fuel reserves, etc. One of the alternatives known as battery operated electric vehicles (BEVs) has the potential to reduce carbon footprints due to lesser or no emissions and thus the focus on shifting people from gasoline operated vehicles (GVs) to BEVs has increased considerably recently. However, BEVs have a limited 'range' and takes considerable time to completely recharge its battery. In addition, charging stations are not as pervasive as gasoline stations. As a result a new fear of getting stranded is observed in BEV drivers, known as range anxiety. Range anxiety has the potential to substantially affect the route choice of a BEV user. It has also been a major cause of lower market shares of BEVs. Range anxiety is a latent feeling which cannot be measured directly. It is not homogenous either and varies among different socio-economic groups. Thus, a better understanding of BEV users' behavior may shed light on some potential solutions that can then be used to improve their market shares and help in developing new network models which can realistically capture effects of varying EV adoptions. Thus, in this study, we analyze the factors that may impact BEV users' range anxiety in addition to their route choice behavior using the integrated choice latent variable model (ICLV) proposed by Bhat and

Dubey (2014). Our results indicate that an individual's range anxiety is significantly affected by their age, gender, income, awareness of charging stations, BEV ownership and other category vehicle ownership. Further, it also highlights the importance of including disutility caused by distance while considering network flow models with combined GV and BEV assignment. Finally, a more concentrated effort can be directed towards increasing the awareness of charging station locations in the neighborhood to help reduce the psychological barrier associated with range anxiety. Overcoming this barrier may help increase consumer confidence, resulting in increased BEV adoption and ultimately will lead towards a potentially pollution-free environment.

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CHAPTER 1: BACKGROUND

Due to economic growth in many developing countries, vehicle ownership is increasing worldwide at an alarming rate. Private car transport has reportedly increased by 25% between 1990 and 2013 (see Zahren, 2012). In 2009, 980 million vehicles were registered worldwide, increasing to 1.015 billion in 2010 (see Sousanis, 2011) (an increase of about 3.6% in just one year). These numbers indicate a trend that supports the predictions of Dargay et al., (2007), who projected that motorized vehicle ownership would exceed 2 billion in 2030. In addition to vehicle market growth, improved infrastructure and driving facilities have also resulted in an increase in daily trip rates per household. The growth in vehicle population and daily trip rates has increased greenhouse gas emissions. This has led to the implementation of policies aimed at promoting relatively more sustainable modes of transportation such as public transit and active modes of transportation (bike and walk) to reduce emissions both by the federal government and metropolitan planning organizations (MPOs). However, in spite of such policies, the share of private vehicles is still very high (see Santos et al., 2011).

One technology that has the potential to reduce the environmental impact of increased driving is the electrification of vehicles, i.e., replacing gasoline power with electrical power. While the first electric vehicle was showcased in the early 1800s, this idea mostly vanished until the late 1990s, when environmental concerns came to the forefront and the concept of alternative fuel vehicles gained worldwide momentum. First, hybrid vehicles (HEVs), fueled by a combination of gasoline and electricity, were introduced, followed by HEVs with larger batteries, known as plug-in electric vehicles (PHEVs), which are charged using the electric grid. However, although HEVs have contributed to the reduction of greenhouse gas emissions, pollution is on the rise due to the increase in overall vehicle ownership and trip rates. Hence, the introduction of pure battery-operated electric vehicles (BEVs) represented potential independence from gasoline and diesel, promising negligible gas emissions and a cleaner environment. These three types of vehicles fall under the general category of *electric vehicles* (EV).

Some organizations are implementing policies favorable for BEVs. California's Air Resource Board is implementing a zero emission vehicle mandate (see news release by California Environmental Protection Agency, 2013). The California Energy Commission provided limited free installations of residential electric charging infrastructure and the federal government has offered rebates and tax credits (see Hartman, 2013), prompting EV market growth. EVs are also becoming popular because of their efficiency, reliability, and low operational costs. These advantages, coupled with the escalation of fuel prices, have caused increased demand for EVs. Further, Navigant Research Group (see Hurst, 2013) forecast that total EV sales by the year 2020 will top 6.5 million. Of this number, around 3 million will be combined sales of PHEVs and BEVs.

One drawback of most BEVs is their limited range[1]. Charging stations are not as pervasive as gasoline stations and charging can take many hours; drivers' fear of being stranded is well-documented. . This fear is commonly termed as *range anxiety*[2]. Apart from the high market price of EVs, several studies found range anxiety to significantly reduce the propensity to purchase BEVs (see Philip and Wiederer, 2010 and Eberle et al., 2010).

Range anxiety has the potential to substantially affect the route choice of an EV user. Specifically, an EV driver's route choice may be quite different from that of a person driving a gasoline vehicle (GV). The disutility caused by range anxiety differentiates the traffic flow of EVs from that of conventional GV. Thus, it is essential to investigate the fundamental question: how does range anxiety affect a driver's route choices? The answer to this question will help in modeling route choice and in forecasting the future heterogeneous traffic flow. However, range anxiety is not homogenous but varies among drivers. We surmise that range anxiety depends on an individual driver's level of risk aversion. Some drivers will be willing to use almost the

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[1] The range of a BEV is the maximum miles that a fully charged BEV can travel between two consecutive charging occasions.

[2] *Range Anxiety* is a term originally coined in the San Diego Business Journal by Richard Acello (1997).

entire range before charging, while others may leave a significant amount of safety margin. This paper tries to capture this varied disutility caused by range anxiety in BEVs. We aim to quantify heterogeneity in range anxiety through a survey and develop a behavior model relating it to driver characteristics. This disutility can then be used to add behavioral realism to the current EV network model (the current models assume deterministic range limits and homogenous drivers). Additional functionality includes the development of new network models that leverage knowledge gained from this study and thus illustrate the system-wide effects of the varying levels of EV adoption.

The remainder of this paper is organized as follows: Section 2 synthesizes earlier literature in relevant areas, identifying the gaps in previous studies to inform this study. Section 3 describes survey instrument design and administration along with sample formation, data cleaning, and variable specification. Sections 4 and 5 define the formulation and estimation employed for this study and the related variables pertaining to individuals. Section 6 elaborate on data analysis using the model described in Section 5 and discusses the analysis findings. Section 7 concludes the paper with a discussion of potential applications of these results.

CHAPTER 2: LITERATURE REVIEW AND MOTIVATION

2.1. EV Market Share and Barriers

Most research on EVs concentrates on the current market share of EVs, factors affecting EV adoption, and forecasts of future market share given the public's attitudes toward EVs. For example, Thiel et al. (2012) discussed the prerequisites for making an EV a popular vehicle choice: reducing the purchase cost, increasing the range, giving more public incentives, and improving the home charging facilities. Bakker (2011) assessed market share based on charging facilities and consumer confidence. Based on optimal pricing strategy, Glerum et al. (2013) evaluated the demand for potential EV technology for the French carmaker Renault. Vehicle purchase price, monthly leasing price, maintenance cost, cost of fuel or electricity, battery rent charges, and incentives offered were the main variables for evaluating the demand. Most of these suggestions have been heeded in subsequent technology development and policies as part of the effort to increase EV adoption.

Using narratives from respondents in a survey, Caperello and Kurani (2011) derived the factors affecting the PHEV market share. Some of the noteworthy factors that favor PHEV adoption are good fuel economy, cost-savings, and reduction of environmental impacts. This study identified the lack of awareness of and uncertainty about relatively new technologies, especially the limited range, as a major barrier to PHEV penetration. Axsen et al., (2009) defined a concept called the 'neighbor effect,' which is the willingness of an individual to buy a vehicle because of its market penetration in his/her neighborhood. They studied the change in the EV market share based on the neighbor effect and also assessed the impact of different policies on the market share. Graham-Rowe et al., (2012) highlighted potential barriers to the PHEV adoption using some new factors: vehicle confidence, perception of an EV as 'work in progress' vehicle, and range restriction that reduces the pleasure of driving. Although these factors were analyzed in the context of EV market share, we hypothesize that similar factors will affect route choices. Some of these factors include range restriction, awareness regarding charging station locations, and comfort with the vehicular technologies.

2.2. CHARGING BEHAVIOR

Some researchers have assessed the current charging behavior of EV users and the impact of EV adoption on the electric grid. A study by Solar Journey USA (see Haaren, 2011) introduced the concept of *sustainable driving*; a term referring to the percentage of trips that can be covered with fully charged EVs. It also considered the factors affecting the electric grid on the basis of distance driven and car usage pattern (with respect to charging and anticipative careful driving), emphasizing the need for smart grid initiatives. Even though this study grazed over the area related to EV driver trips, it did not capture the impact of attitudes (such as range anxiety and an individual's propensity for driving). Also, it did not analyze route choices made by EV drivers since the study's main focus was EV charging patterns and infrastructure requirements. Furthermore, with respect to charging behavior, most of the other studies (see Axsen and Kulkarni, 2009, Jabeen et al., 2013, etc.) that concentrate on charging preferences concluded that people preferred home charging over public charging stations. They further discussed the impact of EVs on the electric grid which highly depends on the time of the day, and stressed the fact that importance should be given to recharge management strategies. All these studies aimed at increasing EV popularity by suggesting favorable policies related to charging infrastructure. A proper study on depicting the travel pattern of EV drivers in terms of driver attitudes remains untouched to date.

2.3. RANGE ANXIETY

Very few studies have analyzed the impact of range anxiety as a psychological barrier to EV adoption. One study (see Franke et al., 2011) defined a comfortable range to overcome psychological barriers, especially the stress buffering behavior of an individual. But this study does not take into account the individual demographics (gender, age, income, etc.) that impact range anxiety. For example, Robinson et al. (2004) observed that females are generally more anxious than males. This was shown by conducting an experiment on undergraduates (37 women and 30 men) in which for the same level of pain, reporting of pain by females were more compared to that by males. The focus of another study (see Franke et al., 2011) was primarily on estimating range anxiety and did not examine its impact on travel behavior. Another study (see Zhang et al., 2012), using a telematics system, estimated the remaining driving range by considering a relationship in which users' range anxiety is inversely proportional to the remaining battery energy. This study concentrated more on the technological and environmental factors impacting range restriction than on the individual's psychology. Though these studies do not explicitly capture the travel pattern changes related to range restriction, they are important since they emphasize consideration of range anxiety in evaluating EV drivers' choices.

To the best of the authors' knowledge, no previous studies have considered the impact of range anxiety and driving propensity on route choices in the context of BEVs[3]. Yet driving propensity will presumably act as an important influencing attitude along with range anxiety in making BEV route decisions. Thus far, an individual's attitudes have been studied for market penetration or vehicle choice determination but not for route choice decisions. This paper's objective is to enhance our knowledge of how BEVs affect travel patterns, particularly because of range restrictions, using attitudinal variables. To some extent, range anxiety is affected both by an individual's demographic characteristics and the vehicle type being driven, while driving propensity is solely affected by demographic characteristics. Since range anxiety and driving propensity are latent feelings associated with an individual and not openly visible or evident, the use of an integrated choice latent variable (ICLV) model (see Bhat and Dubey, 2014) would be ideal. However, our hypothesis is that the effect of an individual's range anxiety on the utility of routes changes with the charge available in a BEV. This variation cannot be captured by the ICLV model. Therefore, we use a modified ICLV model to incorporate this behavior through panel formulation. On the basis of existing literature, the following

[3] *Driving propensity* can be defined as the natural or acquired (over time) tendency of an individual to drive.

factors were used to measure range anxiety: (1) the risk aversion behavior of an individual; (2) awareness of EV charging station locations; (3) importance of vehicular characteristics. For driving propensity, the measurement factors consist of (1) minimum range safety buffer (in miles) evaluated as the difference between the available capacity (displayed in a BEV's charge monitor) and the maximum distance an individual is comfortable driving without re-charging the battery; (2) efforts to carpool or use public transport; (3) importance of vehicular characteristics.

CHAPTER 3: DATA SOURCE AND CONTENT

Due to the limited availability of data representing BEV driver's travel choices, an online survey was developed to generate a data sample[4]. An online survey is the preferred research method for the current study since it has many advantages over other traditional research methods, including eliminating the need for manual data entry, ease in disseminating information regarding the survey, ability to reach a large audience in a short amount of time, smaller margin of errors in entering responses, flexibility in incorporating complicated logic (e.g., irrelevant questions can be automatically skipped for a particular respondent), flexibility in adding animation-based questions, and option of anonymity.

3.1. SURVEY DEVELOPMENT AND ADMINISTRATION

The survey development and administration was divided into three phases. In the first phase, the survey instrument was designed in accordance with the conceptual model and considered previous studies' findings regarding factors affecting BEV travel patterns. After completion of the survey instrument, a series of pre-tests was carried out with some of the staff working at the Center for Transportation Research who fit in the target profile. Revisions were made to the survey instrument based on comments and opinions from these respondents. Through multiple pre-tests, we tried to ensure that the questions are interpreted correctly and there are no discrepancies in any of the questions as viewed by the respondent. The second phase consisted of converting the instrument into an online survey. For this purpose, a survey service software named Qualtrics was used, which permits designing of the survey instrument, distribution of the surveys through various social media sites, data storage and basic data analysis tools. The designed online instrument was dynamic in nature and had a number of complex built-in logics to redirect respondents to relevant sections. It also included randomization of the available choices.

[4] This sample may not be representative of the entire target population. The online format is biased towards people with easy access to the internet, leaving out segments with no internet access. However, since we targeted only people who had driven a car at least once in the past year, our target population most likely had internet access. Therefore, we can safely assume that the sample is a close representation of the actual target population.

After the testing, a pilot survey was carried with a small sample which also contained a few EV owners. The feedback from the pilot survey was used to further improve the survey instrument and address technical problems in the survey. In the last phase, the final survey was activated on April 1, 2014 and included 20–70 questions (taking about 10–20 minutes to complete depending on the respondent's profile). It was conducted by the Center for Transportation Research at The University of Texas at Austin for a period of approximately two months (April 1, 2014–May 27, 2014). No monetary incentive was provided for this survey. The information about the survey was disseminated by various media including flyers, emails and posts on social networking sites apart from snowball sampling. Apart from this, we requested help from several on-line forums, particularly those associated with BEVs, and also groups focused on traffic engineering, demand modeling and automobiles to circulate the survey information. Austin Energy and local metropolitan planning organizations also helped in spreading the survey information.

3.2. Instrument Design

The final questionnaire aimed at capturing the range anxiety experienced by BEV drivers under different hypothetical scenarios and changes in drivers' travel behavior in terms of route choice while driving a BEV versus a GV. To improve the behavioral realism, we have designed the survey instrument using a joint modeling technique, which captures both stated preference and revealed preference. Subsequent questions in the survey consider the responses to the prior questions, using the concept of cognitive method to further improve the behavioral realism of our model.

The questionnaire was divided into a total of four sections. The first section contained general questions related to vehicle ownership, lifestyle, and attitude towards a few attributes that characterize EV use and might impact range anxiety. The second section included questions seeking driver's current travel patterns for commute as well as non-commute trips for each different type of vehicle they own. The third section used hypothetical scenarios to learn about travel patterns while driving a BEV. All questions in this section were based on a hypothetical scenario where an individual was asked to assume that they own a BEV with a randomly generated chosen capacity. Adhering to our speculation that the impact of range anxiety on route choices will differ with the charging left (in miles), we provided three occasions for an individual with different charge limits. We also asked about the individual's preference for charging locations (home, workplace and public charging stations) and reasons for their chosen location. The last section presented general demographic questions.

For this survey, the population was divided into four major categories: respondents owning a gasoline-powered car, respondents owning an HEV, respondents owning a BEV, and respondents who currently do not fall in above categories. Each category has a separate block consisting of set of questions that are most relevant in their situation. Respondents were redirected to the relevant block depending on the chosen category.

3.3. SAMPLE FORMATION AND PROFILE

Various steps were taken to ensure the quality of the survey sample, including removal of incomplete responses and flat-liners[5]. Responses not revealing vehicle ownership details or with total response time of less than 5 minutes were discarded as well. Fields crucial for this study were analyzed and responses with ambiguous replies in these fields were removed. After cleaning the raw data, the final sample included a total of 502 responses from the target audience—adults who have driven a car at least once in the past year in the USA or Canada. The sample contains about 295 (58.8%) males and 311 (62%) workers (full-time (works 35 hours or more per week) or part-time (works less than 35 hours per week)). Respondent ages are equally distributed between 18 and 65 years. Out of 502 individuals, 443 (88.2%) own a GV, 51 (10.2%) own an HEV, 97 (19.32%) own a BEV, and 28 (5.6%) do not currently own any of these vehicle types[6].

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[5] *Flat liners* are the data points that show some definite pattern in answering questions like having the same choice (a, b, c or d) for almost all questions.

[6] The total number of vehicles owned exceeds 502 because some people own more than one vehicle type.

3.4. VARIABLE SPECIFICATION

The route choice model explained in this study considers four route choices depending on varying range restrictions. In order to enhance the predictive power, psychological factors such as range anxiety and driving propensity are also considered in this estimation. A panel version of the integrated choice latent variable (P-ICLV) model, which is a modified version of the Bhat and Dubey's (2014) ICLV model, is used to add behavioral representation. In this estimation, factors affecting range anxiety and driving propensity are age, gender, education, employment status, household income, years of BEV ownership and car ownership. Out of these, factors that affect range anxiety which were found significant comprised of age, gender, income, BEV ownership and Car-ownership. While factors considered significant in influencing driving propensity included age, gender, and education level (refer to Table 5). These factors are called *covariates*. The above latent variables, in turn, are responsible for indicating some of the individuals' behavior patterns. The measure of such behavioral patterns is termed as an *indicator variable*. For the current study, indicators chosen for range anxiety includes the percentage of income an individual is willing to invest in a given hypothetical risky scheme, level of importance an individual gives to vehicular attributes (namely comfort and safety) and an individual's awareness regarding charging station locations. Similarly, indicators that explain driving propensity comprises of minimum range safety buffer[7] an individual is comfortable with, level of importance given to vehicular attributes (namely fuel efficiency, comfort, safety and performance) and concerted effort an individual make to cut down automobile usage by resorting to public transport or carpooling. Apart from individual-specific characteristics, route choice is also based on route attributes. For this study, we considered two crucial variables: total length of the route (distance in miles) and the total travel time for that route (time in seconds). In addition, the route choices are also analyzed using interaction of route attributes with latent variables. Figure 1 provides a complete conceptual picture of the proposed model for BEV route choice.

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[7] In this study, *range safety buffer* is evaluated as the difference between available capacity (displayed in charge monitor of a BEV) and maximum distance an individual is comfortable driving without re-charging the battery.

CHAPTER 4: MODEL FORMULATION

Range anxiety and driving propensity are latent feelings and cannot be measured directly, but can be compared among individuals. Therefore, to see the changes in the route choices due to the latent feeling, we use the ICLV model (see Bhat and Dubey, 2014). Furthermore, our hypothesis is that, an individual's level of range anxiety changes in response to available range limits (in miles). Hence, to analyze the route choices made while driving a BEV, we formulate the panel version of ICLV model (P-ICLV). The proposed P-ICLV model formulation captures the impact of latent feelings on the route choices made by an individual as well as the varied range anxiety across different range limits. This model consists of three components:

1. The latent variable structural equation model;
2. The latent variable measurement equation model; and
3. The panel version of choice model with multiple choice occasions for the same individual.

In the following discussion, we will use the index l for latent variables (l = 1, 2,…,L), index q for the individuals (q = 1, 2,…,Q), k for the choice occasions for each individual (k = 1, 2,…,K), and i for the route choices (i = 1, 2,…,I). For this study, we have L = 2, K = 3 and R = 4, for all decision-makers. Table 3 summarizes the list of all matrices and their dimensions.

4.1. Latent Variable Structural Equation Model

The formulation below has been substantially drawn from Bhat and Dubey (2014), Bhat et al. (2014) and Kamargianni et al. (2014). For the latent variable structural equation model, we will assume that the latent variable z_l^* is a linear function of covariates as follows:

$$z_i^* = \boldsymbol{\alpha}_l' \boldsymbol{w} + \eta_l, \tag{1}$$

where $\boldsymbol{w}$ is a $(\tilde{D}\times 1)$ vector of observed covariates, $\boldsymbol{\alpha_l}$ is a corresponding $(\tilde{D}\times 1)$ vector of coefficients, and η_l is a normally distributed random error term. In our representation, all the latent variables are denoted by the same exogenous vector $\boldsymbol{w}$. This is because; you can always place a value of zero in the appropriate row of $\boldsymbol{\alpha_l}$ if a specific variable does not impact z_l^*. Also, since z_l^* is latent, it will be appropriate to impose the normalization discussed in Stapleton (1978) and implemented by Bolduc *et al.* (2005) by assuming that η_l is standard normally distributed. Next, define the $(L\times\tilde{D})$ matrix $\boldsymbol{\alpha}=(\boldsymbol{\alpha}_1,\boldsymbol{\alpha}_2,...\boldsymbol{\alpha}_L)'$, and the $(L\times 1)$ vectors $\boldsymbol{z^*}=(z_1^*,z_2^*,...,z_L^*)'$ and $\boldsymbol{\eta}=(\eta_1,\eta_2,\eta_3,\ldots,\eta_L)'$. In order to allow correlation among the latent variables, $\boldsymbol{\eta}$ is assumed to be standard multivariate normally distributed: $\boldsymbol{\eta}\sim N[\boldsymbol{0}_L,\boldsymbol{\Gamma}]$, where $\boldsymbol{\Gamma}$ is a correlation matrix (as indicated earlier in Section 1, even though it is typical to enforce the assumption that $\boldsymbol{\eta}$ is diagonal, we do not do so in order to keep the specification general). The matrix representation of Equation (1) is as follows:

$$\boldsymbol{z}^*=\boldsymbol{\alpha w}+\boldsymbol{\eta}. \tag{2}$$

4.2. Latent Variable Measurement Equation Model

For the latent variable measurement equation model, let there be C continuous variables $(y_1,y_2,...,y_C)$ with an associated index c $(c=1,2,...,C)$. Let $y_c=\delta_c+\boldsymbol{d}_c'\boldsymbol{z}^*+\xi_c$ in the typical linear regression fashion, where δ_c is a scalar constant, $\boldsymbol{d_c}$ is an $(L\times 1)$ vector of latent variable loadings on the c^{th} continuous indicator variable. Assume ξ_c to be a normally distributed measurement error term. Load all the C continuous variables into a $(C\times 1)$-vector $\boldsymbol{y}$ and the C constants δ_c into a vector $\boldsymbol{\delta}$ of dimension $(C\times 1)$. Stack all the H error terms into another $(C\times 1)$ vector represented by $\boldsymbol{\xi}=(\xi_1,\xi_2,...,\xi_C)$. Also, assume $\boldsymbol{\Sigma}_y$ be the covariance matrix of $\boldsymbol{\xi}$. Define $\boldsymbol{d}=(\boldsymbol{d_1},\boldsymbol{d_2},...,\boldsymbol{d_C})'$ as the $(C\times L)$ matrix of latent variable loadings. Therefore, the matrix form of the measurement equation for the continuous indicator variables is as follows:

$$\boldsymbol{y} = \boldsymbol{\delta} + \boldsymbol{d}\boldsymbol{z}^{*} + \xi . \tag{3}$$

Similar to the continuous variables, let there also be G ordinal indicator variables, and let g be the index for the ordinal variables $(g = 1, 2, ..., G)$. Let the index for the ordinal outcome category for the g^{th} ordinal variable be represented by j_g. For notational ease only, assume that the number of ordinal categories is the same across the ordinal indicator variables, so that $j_g \in \{1, 2, ..., J\}$. Let y_g^* be the latent underlying variable whose horizontal partitioning leads to the observed outcome for the g^{th} ordinal indicator variable, and let the individual under consideration choose the $n_g{}^{th}$ ordinal outcome category for the g^{th} ordinal indicator variable. Then, in the usual ordered response formulation, we may write: $y_g^* = \tilde{\delta}_g + \tilde{\boldsymbol{d}}_g' \boldsymbol{z}^* + \tilde{\xi}_g$, $\psi_{g,n_g-1} < y_g^* < \psi_{g,n_g}$, where δ_g is a scalar constant, $\tilde{\boldsymbol{d}}_{\boldsymbol{g}}$ is an $(L \times 1)$ vector of latent variable loadings on the underlying variable for the g^{th} indicator variable, and ξ_g is a standard normally distributed measurement error term (the normalization on the error term is needed for identification, as in the usual ordered-response model; see McKelvey and Zavoina, 1975). Note also that, for each ordinal indicator variable, $\psi_{g,0} < \psi_{g,1} < \psi_{g,2} ... < \psi_{g,N_g-1} < \psi_{N_g}$; $\psi_{g,0} = -\infty, \psi_{g,1} = 0$, and $\psi_{g,J} = +\infty$. For later use, let $\boldsymbol{\psi_g} = (\psi_{g,2}, \psi_{g,3}, ..., \psi_{g,J-1})'$, and $\boldsymbol{\psi} = (\boldsymbol{\psi}_1', \boldsymbol{\psi}_2', ... \boldsymbol{\psi}_G')'$. Stack the G underlying continuous variables y_g^* into a $(G \times 1)$ vector $\boldsymbol{y}^*$ and the G constants $\tilde{\boldsymbol{\delta}}_{\boldsymbol{g}}$ into a $(G \times 1)$ vector $\tilde{\boldsymbol{\delta}}$. Also, define the $(G \times L)$ matrix of latent variable loadings $\tilde{\boldsymbol{d}} = \left(\tilde{\boldsymbol{d}}_1, \tilde{\boldsymbol{d}}_2, ..., \tilde{\boldsymbol{d}}_G\right)'$, and let $\boldsymbol{\Sigma}_{y^*}$ be the correlation matrix of $\tilde{\boldsymbol{\xi}} = (\tilde{\xi}_1, \tilde{\xi}_2, ..., \tilde{\xi}_G)$. Stack the lower thresholds $\psi_{g,n_g-1} (g = 1, 2, ..., G)$ into a $(G \times 1)$ vector $\boldsymbol{\psi_{low}}$ and the upper thresholds $\psi_{g,n_g} (g = 1, 2, ..., G)$ into another vector $\boldsymbol{\psi}_{up}$. Then, in matrix form, the measurement equation for the ordinal indicators may be written as:

$$\boldsymbol{y}^* = \tilde{\boldsymbol{\delta}} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\xi}}, \quad \boldsymbol{\psi_{low}} < \boldsymbol{y}^* < \boldsymbol{\psi_{up}} . \tag{4}$$

Define $\breve{\boldsymbol{y}} = \left(\boldsymbol{y}', [\boldsymbol{y}^*]'\right)'$, $\breve{\boldsymbol{\delta}} = (\boldsymbol{\delta}', \tilde{\boldsymbol{\delta}}')'$, $\breve{\boldsymbol{d}} = (\boldsymbol{d}', \tilde{\boldsymbol{d}}')'$, and $\breve{\boldsymbol{\xi}} = (\boldsymbol{\xi}', \tilde{\boldsymbol{\xi}}')'$. Then, the continuous parts of Equations (3) and (4) may be combined into a single equation as:

$$\breve{\boldsymbol{y}} = \breve{\boldsymbol{\delta}} + \breve{\boldsymbol{d}}\boldsymbol{z}^* + \breve{\boldsymbol{\xi}}, \text{ with } \mathrm{E}(\breve{\boldsymbol{y}}) = \begin{bmatrix} \boldsymbol{\delta} + \boldsymbol{d}\boldsymbol{z}^* \\ \tilde{\boldsymbol{\delta}} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* \end{bmatrix}, \text{ and Var } (\breve{\boldsymbol{\xi}}) = \breve{\boldsymbol{\Sigma}} = \begin{bmatrix} \boldsymbol{\Sigma}_y & \boldsymbol{\Sigma}_{\mathbf{yy}^*} \\ \boldsymbol{\Sigma}'_{\mathbf{yy}^*} & \boldsymbol{\Sigma}_{y^*} \end{bmatrix} \tag{5}$$

In this study, there are total 8 indicators comprising of 2 continuous and 6 ordinal indicators, i.e., M = 8, C = 2 and G = 6.

4.3. Choice Model

Let i be the index for routes (i = 1, 2, 3,… I) in a typical random utility-maximizing model. Therefore, the utility for alternative i at occasion k (k=1,2,…,K) for individual q is written as (suppressing the index q):

$$U_{ki} = \boldsymbol{\beta}' \boldsymbol{x}_{ki} + \boldsymbol{\gamma}_i' (\boldsymbol{\varphi}_{ki} \boldsymbol{z}^*) + \varepsilon_{ki}, \tag{6}$$

where $\boldsymbol{x}_{ki}$ is a (D×1)-column vector of exogenous attributes. $\boldsymbol{\beta}$ is a (D×1)-column vector of corresponding coefficients, $\boldsymbol{\varphi}_{ki}$ is an $(N_i \times L)$-matrix of exogenous variables interacting with latent variables to influence the utility of alternative i, $\boldsymbol{\gamma}_i$ is an $(N_i \times 1)$-column vector of coefficients capturing the effects of latent variables and its interaction effects with other exogenous variables, and ε_{ki} is a normal error term that is independent and identically normally distributed across *individuals and choice occasions*. The notation above is very general. Thus, if each of the latent variables impacts the utility of alternative i purely through a constant shift in the utility function, $\boldsymbol{\varphi}_{ki}$ will be an identity matrix of size L , and each element of $\boldsymbol{\gamma}_i$ will capture the effect of a latent variable on the constant specific to alternative i. Alternatively, if the first latent variable is the only one relevant for the utility of alternative i, and it affects the utility of alternative i through both a constant shift as well as an exogenous variable, then N_i =2, and $\boldsymbol{\varphi}_{ki}$ will be a $(2 \times L)$-matrix, with the first row having a '1' in the first column and '0' entries elsewhere, and the second row having the exogenous variable value in the first column and '0' entries elsewhere.[8]

Next, let the variance-covariance matrix of the vertically stacked vector of errors $\boldsymbol{\varepsilon}_k[=(\varepsilon_{k1},\varepsilon_{k2},...,\varepsilon_{kI})']$ be $\boldsymbol{\Lambda}$ and let $\boldsymbol{\varepsilon}[=(\boldsymbol{\varepsilon}_1',\boldsymbol{\varepsilon}_2',...,\boldsymbol{\varepsilon}_K')'](KI\times 1\,\text{vector})$. The covariance of $\boldsymbol{\varepsilon}$ is $\boldsymbol{IDEN_K}\otimes\boldsymbol{\Lambda}$, where $\mathbf{IDEN}_K$ is the identity matrix of size *K*. Define the following vectors and matrices: $\boldsymbol{x}_k=(\boldsymbol{x}_{k1},\boldsymbol{x}_{k2},...,\boldsymbol{x}_{kI})'\,(I\times D\text{ matrix})$, $\boldsymbol{x}=(\boldsymbol{x}_1',\boldsymbol{x}_2',...,\boldsymbol{x}_K')'\,(KI\times D\,\text{matrix})$,

$\boldsymbol{U}_k=(U_{k1},U_{k2},...,U_{kI})'\ (I\times 1\,\text{vector})$, $\boldsymbol{U}=(\boldsymbol{U}_1',\boldsymbol{U}_2',...,\boldsymbol{U}_K')'\ (KI\times 1\,\text{vector})$,

$\boldsymbol{\varphi_\kappa}=(\boldsymbol{\varphi}_{k1}',\boldsymbol{\varphi}_{k2}',...,\boldsymbol{\varphi}_{kI}')'\ \left(\sum_{i=1}^{I}N_i\times L\right)$ matrix, $\boldsymbol{\varphi}=(\boldsymbol{\varphi}_1',\boldsymbol{\varphi}_2',...,\boldsymbol{\varphi}_K')'\ \left(K\sum_{i=1}^{I}N_i\times L\right)$. Also, define the $\left(I\times\sum_{i=1}^{I}N_i\right)$ matrix $\boldsymbol{\gamma}$, which is initially filled with all zero values. Then, position the $(1\times N_1)$ row vector $\boldsymbol{\gamma}_1'$ in the first row to occupy columns 1 to N_1, position the $(1\times N_2)$ row vector $\boldsymbol{\gamma}_2'$ in the second row to occupy columns N_1+1 to N_1+N_2, and so on until the $(1\times N_I)$ row vector $\boldsymbol{\gamma}_I'$ is appropriately positioned. Then, in matrix form, we may write the following equation for the vector of utilities across all choice instances of the individual :

$$\boldsymbol{U}=\boldsymbol{x\beta}+(\boldsymbol{IDEN_K}\otimes\boldsymbol{\gamma})\boldsymbol{\varphi z}^*+\boldsymbol{\varepsilon}=\boldsymbol{x\beta}+\boldsymbol{\lambda z}^*+\boldsymbol{\varepsilon},\ \textbf{\textit{where}}\ \boldsymbol{\lambda}=(\boldsymbol{IDEN_K}\otimes\boldsymbol{\gamma})\boldsymbol{\varphi}\ (KI\times L\,\text{matrix})\quad(7)$$

As in the case of any choice model, one of the alternatives has to be used as the base when introducing alternative-specific constants and variables that do not vary across the *I* alternatives. Also, only the covariance matrix of the error differences is estimable. Taking the difference with respect to the first alternative, only the elements of the covariance matrix $\breve{\boldsymbol{\Lambda}}$ of $\varsigma=(\varsigma_2,\varsigma_3,...,\varsigma_I)$, where $\varsigma_i=\varepsilon_i-\varepsilon_1\ (i\neq 1)$, are estimable. $\boldsymbol{\Lambda}$

[8] In this study, we use unlabeled alternatives (*i.e.*, routes) and thus the route attributes (e.g., travel time, distance, etc.) and latent variables (range anxiety and driving propensity) are introduced purely as interaction terms.

is constructed from $\breve{\mathbf{\Lambda}}$ by adding an additional row on top and an additional column to the left. All elements of this additional row and column are filled with values of zeros. In addition, an additional scale normalization needs to be imposed on $\breve{\mathbf{\Lambda}}$, which may be accomplished normalizing the first element of $\breve{\mathbf{\Lambda}}$ to the value of one.

CHAPTER 5: MODEL SYSTEM IDENTIFICATION AND ESTIMATION

Let $\boldsymbol{\theta}$ be the collection of parameters to be estimated: $\boldsymbol{\theta} = [\text{Vech}(\boldsymbol{\alpha}), \text{Vech}(\boldsymbol{\Gamma}), \breve{\boldsymbol{\delta}}, \text{Vech}(\breve{\boldsymbol{d}}), \boldsymbol{\psi}, \text{Vech}(\breve{\boldsymbol{\Sigma}}), \boldsymbol{\beta}, \text{Vech}(\boldsymbol{\gamma}), \text{Vech}(\breve{\boldsymbol{\Lambda}})]$, where $\text{Vech}(\boldsymbol{\alpha})$, $\text{Vech}(\breve{\boldsymbol{d}})$, and $\text{Vech}(\boldsymbol{\gamma})$ represent vectors of the elements of the $\boldsymbol{\alpha}$, $\breve{\boldsymbol{d}}$, and $\boldsymbol{\gamma}$, respectively, to be estimated, and $\text{Vech}(\boldsymbol{\Gamma})$ represents the vector of the non-zero upper triangle elements of $\boldsymbol{\Gamma}$ (and similarly for other covariance matrices). For future use, define $E = C + G + KI$, and $\tilde{E} = G + (I-1)*K.$

To develop the reduced form equations, we define some additional notations as follows:

$\boldsymbol{\pi} = (\breve{\boldsymbol{d}}', \boldsymbol{\lambda}')'$ ($E \times L$ matrix) , $\vartheta = (\breve{\boldsymbol{\xi}}', \boldsymbol{\varepsilon}')'$ ($E \times 1$ vector) ,

where $\vartheta \sim MVN_E\left[\mathbf{0}_E, \begin{pmatrix} \breve{\boldsymbol{\Sigma}} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Lambda} \end{pmatrix}\right] \sim MVN\left[\mathbf{0}_E, \boldsymbol{\Sigma}\right]$

Now, replace the right side of Equation (1) for $\boldsymbol{z}^*$ in Equations (5) and (7) to obtain the following system:

$$\breve{\boldsymbol{y}} = \breve{\boldsymbol{\delta}} + \breve{\boldsymbol{d}}\boldsymbol{z}^* + \breve{\boldsymbol{\xi}} = \breve{\boldsymbol{\delta}} + \breve{\boldsymbol{d}}(\boldsymbol{\alpha w} + \boldsymbol{\eta}) + \breve{\boldsymbol{\xi}} = \breve{\boldsymbol{\delta}} + \breve{\boldsymbol{d}}\boldsymbol{\alpha w} + \breve{\boldsymbol{d}}\boldsymbol{\eta} + \breve{\boldsymbol{\xi}} \quad (8)$$

$$\boldsymbol{U} = \boldsymbol{x\beta} + \boldsymbol{\lambda z}^* + \boldsymbol{\varepsilon} = \boldsymbol{x\beta} + \boldsymbol{\lambda}(\boldsymbol{\alpha w} + \boldsymbol{\eta}) + \boldsymbol{\varepsilon} = \boldsymbol{x\beta} + \boldsymbol{\lambda\alpha w} + \boldsymbol{\lambda\eta} + \boldsymbol{\varepsilon} \quad (9)$$

Now, consider the $(E \times 1)$ vector $\boldsymbol{YU} = [\breve{\boldsymbol{y}}', \boldsymbol{U}']'$. Define

$$\boldsymbol{YU} = \begin{bmatrix} \breve{\boldsymbol{\delta}} + \breve{\boldsymbol{d}}\boldsymbol{\alpha w} \\ \boldsymbol{x\beta} + \boldsymbol{\lambda\alpha w} \end{bmatrix} + [\boldsymbol{\pi\eta}] + [\vartheta] \quad (10)$$

Then $\boldsymbol{YU} \sim \boldsymbol{MVN}_{C+G+I}(\boldsymbol{B}, \boldsymbol{\Omega})$. (11)

where $\mathbf{B} = \begin{bmatrix} \breve{\boldsymbol{\delta}} + \breve{\boldsymbol{d}}\boldsymbol{\alpha w} \\ \boldsymbol{x\beta} + \boldsymbol{\lambda\alpha w} \end{bmatrix} (E \times 1)$ vector, $\boldsymbol{\Omega} = [\boldsymbol{\pi\eta}] + [\vartheta] (E \times E)$ matrix

General and necessary identification conditions for ICLV models can be found in Bhat *et al.*, (2014) and Bhat (2014).

To estimate the model, we need to develop the distribution of the vector $\boldsymbol{Yu} = \left(\breve{\boldsymbol{y}}', \boldsymbol{u}^{*'}\right)' = \left(\boldsymbol{y}', \boldsymbol{y}^{*'}, \boldsymbol{u}^{*'}\right)'$, where $\boldsymbol{u}^{*} = \left[\left(\mathbf{u}_1^*, \mathbf{u}_2^*, ..., \mathbf{u}_K^*\right)'\right], \mathbf{u}_t^* = \left(u^*_{k1m_t}, u^*_{k2m_t}, ..., u^*_{kIm_t}\right)'$, $u^*_{kim_t} = U_{ki} - U_{km_k} (i \neq m_k)$, and m_k indicates the chosen alternative at choice occasion *k*. To do so, define a matrix $\mathbf{M}$ of size $\left[C + G + (I-1) * K\right] \times \left[C + G + KI\right]$. Fill this matrix up with values of zero. Then, insert an identity matrix of size $C + G$ into the first $C + G$ rows and $C + G$ columns of the matrix $\mathbf{M}$. Next, consider the last $(I-1)*K$ rows and KI columns of the matrix $\mathbf{M}$. **P**osition a block-diagonal matrix in these rows and columns, each block diagonal being of size $\left[(I-1) \times I\right]$ and containing the matrix $\mathbf{M}_k$, which itself is an identity matrix of size (*I*-1) with an extra column of '-1' values added at the m_k^{th} column. Then, we can write $\boldsymbol{Yu} \sim \boldsymbol{MVN}_{C+G+(I-1)*K}(\tilde{\boldsymbol{B}}, \tilde{\boldsymbol{\Omega}})$, where $\tilde{\boldsymbol{B}} = \mathbf{M}\boldsymbol{B}$ and $\tilde{\boldsymbol{\Omega}} = \mathbf{M}\boldsymbol{\Omega}\mathbf{M}'$. Next, partition the vector $\tilde{\boldsymbol{B}}$ into components that correspond to the mean of the vectors $\boldsymbol{y}, \boldsymbol{y}^*$, and $\boldsymbol{u}^*$, and the matrix $\tilde{\boldsymbol{\Omega}}$ into the variances of $\boldsymbol{y}, \boldsymbol{y}^*$, and $\boldsymbol{u}^*$ and their covariances:

$$\tilde{\boldsymbol{B}} = \begin{bmatrix} \tilde{\boldsymbol{B}}_y \\ \tilde{\boldsymbol{B}}_{y^*} \\ \tilde{\boldsymbol{B}}_{u^*} \end{bmatrix} \text{ and } \tilde{\boldsymbol{\Omega}} = \begin{bmatrix} \tilde{\boldsymbol{\Omega}}_y & \tilde{\boldsymbol{\Omega}}_{yy^*} & \tilde{\boldsymbol{\Omega}}_{yu^*} \\ \tilde{\boldsymbol{\Omega}}'_{yy^*} & \tilde{\boldsymbol{\Omega}}_{y^*} & \tilde{\boldsymbol{\Omega}}_{y^*u^*} \\ \tilde{\boldsymbol{\Omega}}'_{yu^*} & \tilde{\boldsymbol{\Omega}}'_{y^*u^*} & \tilde{\boldsymbol{\Omega}}_{u^*} \end{bmatrix} \tag{12}$$

Define $\tilde{\boldsymbol{u}} = \left(\boldsymbol{y}^{*'}, \boldsymbol{u}^{*'}\right)'$, so that $\boldsymbol{Yu} = (\boldsymbol{y}', \tilde{\boldsymbol{u}}')'$. Re-partition $\tilde{\boldsymbol{B}}$ and $\tilde{\boldsymbol{\Omega}}$ in a different way such that:

$$\tilde{\boldsymbol{B}} = \begin{bmatrix} \tilde{\boldsymbol{B}}_y \\ \tilde{\boldsymbol{B}}_{\tilde{u}} \end{bmatrix} ((C + \tilde{E}) \times 1) \text{ vector, where } \tilde{\boldsymbol{B}}_{\tilde{u}} = \begin{bmatrix} \tilde{\boldsymbol{B}}_{y^*} \\ \tilde{\boldsymbol{B}}_{u^*} \end{bmatrix} (\tilde{E} \times 1) \text{ vector, and} \tag{13}$$

$$\tilde{\boldsymbol{\Omega}} = \begin{bmatrix} \tilde{\boldsymbol{\Omega}}_y & \tilde{\boldsymbol{\Omega}}_{y\tilde{u}} \\ \tilde{\boldsymbol{\Omega}}'_{y\tilde{u}} & \tilde{\boldsymbol{\Omega}}_{\tilde{u}} \end{bmatrix} (C + \tilde{E}) \times (H + \tilde{E}) \text{ matrix, where } \tilde{\boldsymbol{\Omega}}_{\tilde{u}} = \begin{bmatrix} \tilde{\boldsymbol{\Omega}}_{y^*} & \tilde{\boldsymbol{\Omega}}_{y^*u^*} \\ \tilde{\boldsymbol{\Omega}}'_{y^*u^*} & \tilde{\boldsymbol{\Omega}}_{u^*} \end{bmatrix} (\tilde{E} \times \tilde{E}) \text{ matrix,}$$

and $\tilde{\boldsymbol{\Omega}}_{y\tilde{u}} = \left[\tilde{\boldsymbol{\Omega}}_{yy^*} \quad \tilde{\boldsymbol{\Omega}}_{yu^*}\right]$

The conditional distribution of $\tilde{\boldsymbol{u}}$, given $\boldsymbol{y}$, is multivariate normal with mean $\ddot{\boldsymbol{B}}_{\tilde{u}} = \tilde{\boldsymbol{B}}_{\tilde{u}} + \tilde{\boldsymbol{\Omega}}'_{y\tilde{u}}\, \tilde{\boldsymbol{\Omega}}_y^{-1}\left(\boldsymbol{y} - \tilde{\boldsymbol{B}}_y\right)$ and variance $\ddot{\boldsymbol{\Omega}}_{\tilde{u}} = \tilde{\boldsymbol{\Omega}}_{\tilde{u}} - \tilde{\boldsymbol{\Omega}}'_{y\tilde{u}}\, \tilde{\boldsymbol{\Omega}}_y^{-1} \tilde{\boldsymbol{\Omega}}_{y\tilde{u}}$. Next, supplement the threshold vectors defined earlier as follows: $\tilde{\boldsymbol{\psi}}_{\boldsymbol{low}} = \left[\boldsymbol{\psi}'_{\boldsymbol{low}}, \left(-\boldsymbol{\infty}_{(I-1)*K}\right)',\right]'$, and $\tilde{\boldsymbol{\psi}}_{\boldsymbol{up}} = \left[\boldsymbol{\psi}'_{up}, \left(\boldsymbol{0}_{(I-1)*K}\right)'\right]'$, where $-\boldsymbol{\infty}_{(I-1)*K}$ is an $(I-1)*K \times 1$-column vector of negative infinities, and $\boldsymbol{0}_{(I-1)*K}$ is another $(I-1)*K \times 1$-column vector of zeros. Then the likelihood function may be written as:

$$
\begin{aligned}
L(\boldsymbol{\theta}) &= f_C(\boldsymbol{y} - \tilde{\boldsymbol{B}}_y \,|\, \tilde{\boldsymbol{\Omega}}_y) \times \Pr\left[j_1 = n_1, j_{2'} = n_2, \dots, j_G = n_G; m_1, m_2, \dots m_K\right] \\
&= f_C(\boldsymbol{y} - \tilde{\boldsymbol{B}}_y \,|\, \tilde{\boldsymbol{\Omega}}_y) \times \int_{D_{\tilde{u}}} f_{G+(I-1)*K}(\tilde{\boldsymbol{u}} \,|\, \ddot{\boldsymbol{B}}_{\tilde{u}}, \ddot{\boldsymbol{\Omega}}_{\tilde{u}})\, d\tilde{\boldsymbol{u}}
\end{aligned} \tag{14}
$$

where $D_{\tilde{u}}$ is the region of integration such that $D_{\tilde{u}} = \{\tilde{\mathbf{u}} : \tilde{\boldsymbol{\psi}}_{low} \le \tilde{\mathbf{u}} \le \tilde{\boldsymbol{\psi}}_{up}\}$. $f_{G+(I-1)*K}(.)$ is the multivariate normal density function of dimension $G + (I-1)*K$. The above likelihood function involves the evaluation of a $G + (I-1)*K$ (15 in the current study; 6 ordinal variable + 4 routes + 3 choice occasions) dimensional integral for each individual, which can be computationally expensive. So, the Maximum Approximate Composite Marginal Likelihood (MACML) approach of Bhat (2011), in which the likelihood function only involves the computation of univariate and bivariate cumulative distributive functions, is used in this paper.

In the context of the proposed model, consider the following (pairwise) composite marginal likelihood function:

$$
\mathrm{L}_{\mathrm{CML}}(\boldsymbol{\theta}) = \mathrm{f}_{\mathrm{C}}(\boldsymbol{y} - \tilde{\boldsymbol{B}}_y \,|\, \tilde{\boldsymbol{\Omega}}_y) \times \left[\begin{array}{l} \left(\prod_{g=1}^{G-1} \prod_{g'=g+1}^{G} \Pr(\mathrm{j_g} = \mathrm{n_g}, \mathrm{j_{g'}} = \mathrm{n_{g'}}) \right) \times \left(\prod_{g=1}^{G} \prod_{k=1}^{K} \Pr(\mathrm{j_g} = \mathrm{n_g}; \mathrm{m_k}) \right) \\ \times \left(\prod_{k=1}^{K-1} \prod_{k'=k+1}^{K} \Pr(\mathrm{m_k}; \mathrm{m_{k'}}) \right) \end{array} \right] \tag{15}
$$

In the above CML approach, the MVNCD function appearing in the CML function is of dimension equal to two for $\Pr(j_g = n_g, j_{g'} = n_{g'})$ (corresponding to the probability of each pair of observed ordinal indicators), equal to I for $\Pr(j_g = n_g; m_k)$ (corresponding to each combination of an ordinal indicator and the observed choice outcome at a specific occasion *k*), and equal to $2(I-1)$ for $\Pr(m_k, m_{k'})$ (corresponding to each combination of observed choice outcome at time period *k* and time period *k'*). To explicitly write out the CML function in terms of the standard and bivariate standard normal density and cumulative distribution function, define $\boldsymbol{\omega}_{\Delta}$ as the diagonal matrix of standard deviations of matrix $\boldsymbol{\Delta}$, $\phi_R(.;\boldsymbol{\Delta}^{**})$ for the multivariate standard normal density function of dimension *R* and correlation matrix $\boldsymbol{\Delta}^*$ ($\boldsymbol{\Delta}^* = \boldsymbol{\omega}_{\Delta}^{-1}\boldsymbol{\Delta}\boldsymbol{\omega}_{\Delta}^{-1}$), and $\Phi_E(.;\boldsymbol{\Delta}^*)$ for the multivariate standard normal cumulative distribution function of dimension *E* and correlation matrix $\boldsymbol{\Delta}^*$. Now, define the following matrices: (1) A selection matrix $\mathbf{A}_{gk}$ (*g*=1,2,…*G* and *k*=1,2,…,*K*) of dimension $(I \times \widetilde{E})$: Fill this matrix with values of zero for all elements and then, position an element of '1' in the first row and the g^{th} column. Also, position an identity matrix of size $I-1$ in the last $I-1$ rows and columns from $G+(I-1)(k-1)+1$ to $G+(I-1)k$, (2) A selection matrix $\mathbf{R}_{kk'}$ $(k,k'=1,2,\ldots K,\ k \neq k')$ of dimension $[2*(I-1)] \times \widetilde{E}$: Fill this matrix with values of zero for all elements. Then, insert an identity matrix of size $I-1$ in rows 1 to $(I-1)$ and columns $G+(I-1)(k-1)+1$ to $G+(I-1)k$. Similarly, position another identity matrix of size $I-1$ in the rows $(I-1)+1$ to $2*(I-1)$ and columns $G+(I-1)(k'-1)+1$ to $G+(I-1)\,k'$. Let $\widehat{\psi}_{\text{g,up}} = \dfrac{\left[\tilde{\boldsymbol{\psi}}_{\boldsymbol{up}}\right]_{\text{g}} - \left[\vec{\boldsymbol{B}}_{\tilde{\text{u}}}\right]_{\text{g}}}{\sqrt{\left[\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\right]_{\text{gg}}}}$, $\widehat{\psi}_{\text{g,low}} = \dfrac{\left[\tilde{\boldsymbol{\psi}}_{\text{low}}\right]_{\text{g}} - \left[\vec{\boldsymbol{B}}_{\tilde{\text{u}}}\right]_{\text{g}}}{\sqrt{\left[\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\right]_{\text{gg}}}}$, $\upsilon_{gg'} = \dfrac{\left[\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\right]_{gg'}}{\sqrt{\left[\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\right]_{gg} * \left[\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\right]_{g'g'}}}$,

$\breve{\boldsymbol{\psi}}_{g,\boldsymbol{low}} = \left[\left[\tilde{\boldsymbol{\psi}}_{\boldsymbol{low}}\right]_g, \left(-\boldsymbol{\infty}_{(I-1)}\right)'\right] (I \times 1)$ vector, $\breve{\boldsymbol{\psi}}_{g,\boldsymbol{up}} = \left[\left[\tilde{\boldsymbol{\psi}}_{\boldsymbol{up}}\right]_g, \left(\mathbf{0}_{(I-1)}\right)'\right] (I \times 1)$ vector,

$\breve{\boldsymbol{B}}_{gk} = \mathbf{A}_{gk}\vec{\boldsymbol{B}}_{\tilde{u}}$, $\breve{\boldsymbol{\Omega}}_{gk} = \mathbf{A}_{gk}\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\mathbf{A}'_{gk}$, $\widehat{\boldsymbol{B}}_{kk'} = \mathbf{R}_{kk'}\vec{\boldsymbol{B}}_{\tilde{u}}$, $\widehat{\boldsymbol{\Omega}}_{kk'} = \mathbf{R}_{kk'}\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\mathbf{R}'_{kk'}$, where $\left[\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{\boldsymbol{u}}}\right]_{gg}$

represents the gg^{th} element of the matrix $\overleftrightarrow{\mathbf{\Omega}}_{\tilde{\boldsymbol{u}}}$. Then, the CML function to be maximized is:

$$
\begin{aligned}
L_{CML}(\boldsymbol{\theta}) = & \left(\prod_{\mathrm{h}=1}^{\mathrm{H}} \omega_{\tilde{\mathbf{\Omega}}_y} \right)^{-1} \phi_C \left(\left[\omega_{\tilde{\mathbf{\Omega}}_y} \right]^{-1} \left[\boldsymbol{y} - \tilde{\boldsymbol{B}}_y \right]; \tilde{\mathbf{\Omega}}_y^* \right) \times \\
& \left(\prod_{g=1}^{G-1} \prod_{g'=g+1}^{G} \begin{bmatrix} \Phi_2(\hat{\psi}_{g,up}, \hat{\psi}_{g',up}, \upsilon_{gg'}) - \Phi_2(\hat{\psi}_{g,up}, \hat{\psi}_{g',low}, \upsilon_{gg'}) \\ -\Phi_2(\hat{\psi}_{g,low}, \hat{\psi}_{g',up}, \upsilon_{gg'}) + \Phi_2(\hat{\psi}_{g,low}, \hat{\psi}_{g',low}, \upsilon_{gg'}) \end{bmatrix} \right) \times \\
& \left(\prod_{g=1}^{G} \prod_{k=1}^{K} \left(\Phi_1 \left[\left(\breve{\boldsymbol{\psi}}_{\boldsymbol{g,up}} - \breve{\boldsymbol{B}}_{gk} \right) \boldsymbol{\omega}^{-1}_{\breve{\mathbf{\Omega}}_{gk}}; \boldsymbol{\omega}^{-1}_{\breve{\mathbf{\Omega}}_{gk}} \breve{\mathbf{\Omega}}_{gk} \, \boldsymbol{\omega}^{-1}_{\breve{\mathbf{\Omega}}_{gk}} \right] - \Phi_1 \left[\left(\breve{\boldsymbol{\psi}}_{\boldsymbol{g,low}} - \breve{\boldsymbol{B}}_{gk} \right) \boldsymbol{\omega}^{-1}_{\breve{\mathbf{\Omega}}_{gk}}; \boldsymbol{\omega}^{-1}_{\breve{\mathbf{\Omega}}_{gk}} \breve{\mathbf{\Omega}}_{gk} \, \boldsymbol{\omega}^{-1}_{\breve{\mathbf{\Omega}}_{gk}} \right] \right) \right) \times \\
& \left(\prod_{k=1}^{K-1} \prod_{k'=k+1}^{K} \Phi_{2*(\mathrm{I}-1)} \left[(\boldsymbol{\omega}^{-1}_{\hat{\mathbf{\Omega}}_{kk'}})(-\hat{\boldsymbol{B}}_{kk'}); \boldsymbol{\omega}^{-1}_{\hat{\mathbf{\Omega}}_{kk'}} \hat{\mathbf{\Omega}}_{kk'} \boldsymbol{\omega}^{-1}_{\hat{\mathbf{\Omega}}'_{kk}} \right] \right), \qquad (16)
\end{aligned}
$$

In the above expression, an analytic approximation approach is used to evaluate the MVNCD functions in the second, third, and fourth elements (this analytic approach is embedded within the MACML approach of Bhat, 2011).

CHAPTER 6: RESULTS

6.1. Structural Equation Estimates

6.1.1 Range Anxiety

As seen in Table 5, age and gender have a significant impact on both latent variables (range anxiety and driving propensity). According to the results, range anxiety first increases (up to 64 years) and then decreases (65 and above) with the age. Several other studies on anxiety (see Soto et al., 2011; Regier et al., 1993; Carta et al., 1991; Lehtinen et al., 1990; Bland et al., 1988; and Weissman and Myers, 1980) also found a trend where anxiety increases with age up until a point and then decreases after a particular age[9]. Most of these studies have reported that the range anxiety of a person increases with age until 64 years and then decreases. One possible explanation is that the younger population experiences less stress due to absence of economic hardships (see Drentea, 2000) and hence experience low anxiety. The addition of family or financial responsibilities increases an individual's anxiety engendering more conservative behavior. As a person grows older, her/his responsibilities are transferred to the next generation, thus decreasing stress and anxiety levels. Also, some psychological studies suggest a decreased responsiveness to negative emotions and an increased sense of emotional control beyond a certain age (see Soto et al., 2011; O'Connor and Parslow, 2009; Gross *et al*., 1997 and Levenson et al., 1991). This decreased range anxiety can be explained by term called *psychological immunization,* which refers to the coping abilities developed during a lifetime of adverse events.

Our results show that the people who own a vehicle experience less range anxiety as compared with people who currently do not own any vehicle. Possibly non-owners do not have much experience or comfort with driving a vehicle (current technology) and hence exhibit more anxiety when adapting to new technology (see Mick and Fournier, 1998). This pattern, however, is the opposite for participants switching from a

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9 This peak age is different in one of the studies. According to Bland et al. (1988), Carta et al. (1991), and Regier et al. (1993), the peak age is 65, while Lehtinen et al. (1990) places it at 80.

conventional vehicle (an existing technology) to a BEV (a modified technology). In this case, individuals are first excited about substituting a conventional vehicle with a BEV and are not fully aware of the consequences of limited range. They initially have less knowledge about the accuracy of the charge meter and factors affecting charge dissipation. Hence, they completely trust the predicted distance displayed by the BEV charge meter. Perhaps this lack of knowledge is the source of the higher propensity for risk among consumers driving electric cars. However, as they become more educated regarding the workings and shortcomings of the battery, they start to experience increased range anxiety. Later, as they build up years of experience with BEV ownership, drivers again become comfortable with the new technology and experience reduced range anxiety (see Ferreira et al., 2014). Our results support the premise that BEV owners experience more range anxiety than non-BEV owners. Due to the lack of sufficient data points for the individuals with less than one year of BEV ownership and more than one year of BEV ownership, we found the difference between their range anxieties to be insignificant. However, we did find the trend of decreasing range anxiety with increasing length of BEV ownership. Enough sample size for both these characteristic populations could have confirmed our hypothesis that the range anxiety decreases with increase in length of BEV ownership.

According to previous studies, males are observed to have low willingness to report pain or discomfort compared to females (see Robinson et al., 2000; Chiavegatto Filho et al., 2013). Hence, when compared to females, males report less anxiety but the reason behind this gender-stereotyped behavior towards the perception of pain is still unknown. Surprisingly, our results show that males have more range anxiety when compared to other gender categories, in contrast to the study by Robinson et al. (2004). This might be because our sample has a smaller number of females owning a BEV (6.28%) and this bias in the sample may be the reason behind low range anxiety among females. Also, previous studies (see Chiavegatto Filho et al., 2013; Ginsburg et al., 2002) noted that low-income populations experience greater anxiety, as compared to high-income groups, due to instability and high stress. The relationship between income and general anxiety was often found to be statistically insignificant. However, our results suggest that the household income is significantly associated with range anxiety. We found that the lower-income group exhibits less anxiety when compared with higher-income groups; as the income increases further, the range anxiety decreases. The initial drop in range anxiety for the low-income group may be explained by the fact that our low-income group sample consists primarily (70.4%) of traditional vehicle owners (who experience low range anxiety compared to people who do not own any vehicle or own a BEV); only 1.4% of the low-income group own BEVs.

6.1.2 Driving Propensity:

In terms of driving propensity, no particular pattern was found according to age. Notably, however, respondents between 25 and 34 years show comparatively lower affinity for driving. Strangely, respondents over 64 years of age tended to have a comparatively higher driving propensity. Perhaps older people, due to their physical condition, find biking, walking or the use of public transport more strenuous, and hence prefer driving over other alternatives. Meanwhile, the younger generation is becoming more aware of the impacts of driving conventional vehicles on the environment and the benefits of using public transport. One might argue that switching to a BEV would also act as a viable alternative for solving eco-friendly problems but some of the barriers of buying a BEV (e.g., affordability, limited range, higher charging time) are hampering the BEV ownership among younger population especially students and people in their settling phase (between years 18–35). With respect to age, similar trends were reported by Davis et al. (2012), who found that the miles traveled per year by an average American decreased by 6% from 2004 to 2011. They also reported a drop of 23% from 2001 to 2009 in the average annual number of vehicle miles traveled by young people (16-34 years olds). The potential explanations for this drop includes the 2008-2009 recession, fuel price increases, strict enactment of Graduated drivers' Licensing laws, and changes in people's preferences and priorities (see Davis et al., 2012). One of the major causes of decreased driving behavior among younger population may be due to the increase in fuel prices and advances in technology that have resulted in increased reliability of public transportation (see Davis et al., 2012). These factors are instigating people to shift to public transportation as well as car and bike sharing alternatives, which are comparatively cheaper and readily available (especially in cities). According to the NHTS[10] surveys in 2001 and 2009, there was about a 40% increase in the number of miles taken by public transit by individuals between ages 16 and 34. In addition to this, the percentage of work from home opportunities must have decreased travel demand. Our study indicates that males have a higher tendency to drive relative to females. A similar trend was found for driving propensity in a travel behavior report (see Mattson et al., 2012) based on the 2009 National Household Travel Survey (NHTS). According to the report, in the 19-64 age group, around 91.3% of males and 90.9% of females drive a personal vehicle. For older people, this gap was found to further increase. It is expected that men acquire more propensity toward driving when compared with women. This might be because percentage of employment in men is more than in women and hence they make daily work trips. Some of them might even trip-chain regular household activities (like grocery shopping, picking up children, etc.), further adding miles driven using a vehicle. Further, our study found that more educated people have less inclination to drive, possibly due to the increased environmental awareness that often accompanies higher levels of education. Also, highly educated people tend to be more invested in their careers and have heavier workloads, and thus would opt to reduce commute time by living in more expensive urban areas. Since they are likely to have high paying jobs, business trips are often made by air flights or company driven vehicle. All these factors might affect their driving propensity.

6.1.3 Correlation:

There is a significant correlation (with a value of -0.4) between the two latent variables – range anxiety and driving propensity. The negative value of correlation is

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10 The National Household Travel Survey (NHTS) is a survey funded by the Federal Highway Administration and conducted every 5 to 10 years.

reasonable, since the range anxiety often hampers a person's decision to drive for long hours or long distance. But driving propensity, which is associated with the inherent or acquired inclination towards driving, would press a person to drive for long distances. Due to the fear of getting stranded in between of a trip, an individual would prefer to choose shorter routes or even not prefer to drive. But, if a person has a strong pro-driving attitude, then he may get over his fear a bit and may be willing to drive extra miles.

6.2. INDICATORS

Latent feelings influence an individual's decision and behavior. Such decisions or behavior which captures the effect of latent variables are called indicators[11]. One of the main indicators for range anxiety used in this study is an individual's risk related decisions. A recent study by Giorgetta et al. (2012) revealed that anxiety, which is often associated with restlessness, insecurity, tense environment, etc., also affects the risk-taking behavior of an individual. Anxiety often restrains risky behavior, as confirmed by many psychological studies (see Maner & Schmidt, 2006; Maner et al., 2007; Mitte, 2007; Eisenberg et al., 1998). Our study also confirms that drivers with high range anxiety are risk-averse in terms of range limits (see Table 6) and tend to avoid trips that will nearly exhaust their battery charge. A similar correlation was found for range anxiety with respect to the importance placed on comfort and vehicle safety features when purchasing a vehicle. More anxious drivers place less importance on comfort since they would be more concerned about the vehicle's range limit. In fact, using vehicular comfort features such as the radio and air-conditioner in a BEV exhausts the battery at faster rate. Although, many studies noted that anxiety is positively related and risk attitude is negatively related with the safety preferences of an individual (see Chen, 2009), anxiety was found to be negatively correlated with the safety features of the vehicle. One reason

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[11] The variance ($\boldsymbol{\Sigma}_y$) and the threshold ($\psi_{g,j}$) values of the continuous and ordinal indicator variables are provided in the Table 8. The variance for continuous indicator and the threshold for ordinal indicators as such do not have any tangible interpretation. The thresholds are simply used to map the calculated $\boldsymbol{y}^*$ values to corresponding categories of the ordinal variables. Furthermore, we fixed the scale of ordinal variable by fixing the second threshold to 0 (first threshold being -∞) and hence only remaining thresholds (g - 2) needs to be estimated.

could be that safety concerns (in respect to vehicle purchase) are more related to vehicular safety than to personal safety, which people might rate low when compared with other features like performance and range limit. Experiments done by TEPCO and BMW Mini E show the importance of public charging stations (especially fast charging stations) in relieving range anxiety (see Bakker, 2011). On similar grounds, the availability of regular public charging stations and awareness regarding the locations of charging stations is equally important to moderate the range concern. An area with minimal charging infrastructure tends to make an individual more anxious. Additionally, prior knowledge of charging station locations would decrease uncertainty about reaching the destination safely. Our study suggests similar behavior, i.e., the more people are aware of charging station locations, the lower their range anxiety.

A straightforward measure for driving propensity would be how long a person is willing to drive given the range limitation. A person who is keen to travel until the range is close to exhaustion (given no charging options in between) would leave less buffer. As expected, our study showed a negative correlation between driving propensity and the minimum safety buffer for range. In addition, individuals who are more inclined towards driving placed higher importance on vehicular features. Furthermore, our study also suggests that among all these features (such as fuel efficiency, comfort, safety, and overall performance), comfort dominates other features, followed by performance. This finding is not surprising since the people with pro-driving attitudes would generally go for long drives, and for long distance travel, comfort and performance of the vehicle would be of prime importance. Our analysis also reveals the negative correlation between an individual's driving propensity and individual's efforts to reduce traffic through carpooling or using public transportation. It is very natural for a person who likes driving to choose to drive a vehicle personally instead of shifting to public transportation or carpooling.

6.3. Choice Model Results

Our analysis, provided in Table 7, suggests that both range anxiety and driving propensity significantly affect route choices made by an individual. As expected, range availability during travel would act as a utility while distance and travel time of a route acts a disutility when deciding between routes. Although most individuals will always try to choose route such that it is short as well as fast (can travel with more speed or less congested), the weightage given to each route attribute differs with the attitude of the individual. For an individual with a high level of range anxiety, long distance travel adds more disutility compared to short distance travel. This is natural since the person with higher anxiety would be more worried about not completing the trip before the battery completely depletes. Therefore, longer distance would make her/him nervous and hence add extra disutility. However, a person experiencing low range anxiety would not experience stress due to length of the route. Therefore, the disutility caused by distance for all routes is almost same. A similar trend is seen in the interaction of range anxiety with the travel time. The person who currently experiences higher range anxiety will try to limit their travel time to a small value. That individual will choose the less congested route in order to decrease the period of uncertainty caused by the BEV's limited range. In terms of driving propensity, it might seem strange that even for the people who prefer driving, distance causes additional discomfort. In fact, the results indicate that those with higher driving propensity prefer shorter paths over longer ones, yet this extra discomfort due to distance is minuscule for a person with low driving propensity. With respect to travel time, a similar trend as reported for distance is observed, which would not be surprising since one of the reasons why people prefer driving over using other means of transport would be to save time. Therefore, an individual who is more inclined towards driving experiences increased discomfort due to travel time as opposed to one who is less inclined towards driving. As we can see, the additional disabilities are caused by attitudes of an individual which are significant and hence needs consideration in current network models. Failure to incorporate these attitudinal variations would result in erroneous representation of EV traffic flow.

6.4. ELASTICITY ANALYSIS

The parameter values presented in Table 5 through Table7 are used to inspect the effects of latent variables as well as route attributes on route choice. There is a significant difference between the probabilities of choosing a route obtained when (1) we consider interactions with range anxiety and driving propensity (2) we do not consider these interactions. On considering the interactions of route attributes with the latent variables, the probability of choosing a path having route length 15% more than the other route (all other attributes being same) is 33.91%, while it is 34.2% (0.29% more) in the absence of interaction term. This shows that the interactions add certain amount of disutility with respect to the distance. Furthermore, on examining the effects of route attributes, our study found that the probability of choosing a path with travel time 15% more than the other route is 35.76% (which is 1.85% more than that obtained by 15% increase in length). This suggests that the sensitivity of route choice with respect to route's length is slightly more compared to its travel time. In traditional models (especially static traffic assignment models) used by most of the US metropolitan planning organizations, the disutility caused by distance receives less importance or is often ignored. In such models, major importance is given to disutility produced by travel time. However, above analysis suggests that while considering demand which includes EVs, ignoring the impact of distance on route choices may produce biased results. There is a need to include the disutility caused by distance along with the effects of individual's latent behavior.

CHAPTER 7: CONCLUSION AND APPLICATION

This paper presents a model for estimating the impact of psychological factors like range anxiety and driving propensity on routes choices while using a BEV. The study contributes to a new direction in the area of integration of the EV range restrictions with the travel behavior of an individual. It contributes to the existing literature in the following ways: First, the number of BEVs on the road is on the rise, and it is essential that these vehicles be properly accounted for in planning the transportation infrastructure of the future. Currently, in route choice modeling, the EVs are treated as traditional vehicles with fixed distance constraints to reflect range restrictions. There is a need to represent the heterogeneity of such vehicles in network models. Second, very little effort has been devoted nationally to assessing how BEV drivers change their behavior and this is the first attempt to analyze the impact of one of the important barriers associated with EVs, viz. range anxiety on their travel pattern. Third, the study determines the cautiousness of BEV drivers and characteristics which can be connected to their travel decisions in order to include BEVs into modern and future transportation network models.

Due to the limited availability of data on BEV users' travel choices, a dynamic online survey was designed using a joint modeling technique which captures both stated and revealed preferences. To improve the behavioral realism, the concept of 'cognitive method' was used for survey-instrument designing where options in later questions were designed based on the choices selected in previous questions. Empirical results in this paper show that there is a significant impact of range restrictions on drivers' route choices while driving a BEV. While time is of essence in traditional network models, due to this new restriction, there is now a tradeoff between distance and travel time which needs consideration. The research highlights the importance of distance as a disutility in route choice. In addition, the study also offers several key insights regarding the factors affecting range anxiety. It confirms that there is still some concern regarding the limited range reserve. Awareness of charging station locations plays an important role in reflecting the anxiety level of an individual. Lesser the people are aware of charging locations; more will there be range anxiety resulting in increased discomfort in switching to EVs. Another interesting finding is how the anxiety level changes with age and longevity of BEV ownership. It has been observed that range anxiety is more in individuals with ages in between 35 to 65 years. Also, the range anxiety of an individual initially increases with the purchase of a BEV and then decreases with the years of BEV ownership. Our study proposes a more concentrated effort can be directed towards increasing the awareness of charging station locations in the neighborhood to help reduce the psychological barrier associated with range anxiety. Overcoming this barrier may help increase consumer confidence, resulting in increased EV adoption and ultimately lead towards a potentially pollution-free environment in the future.

Further research is needed in this field to get nearly accurate range anxiety representation in future transportation network models. Especially, the efficiency of the battery is hampered by environmental factors (e.g., cold or hot climate, snowy or rainy season, etc.), physical attributes of routes (e.g., slope, grade, etc.) and usage of vehicular comfort features (e.g., AC, heater, radio, etc.). Consideration of all these factors will result in more realistic representation of the influence of range anxiety. Spatial analyses might be more relevant in this context to capture the actual effect of climatic conditions on range anxiety. Nevertheless, this paper models the heterogeneity in range limits and individual preferences/behavior when constrained by reserved range and accentuating the need to incorporate this behavior in future network models. It also provides important insights which would be valuable in planning guiding policies for decreasing the discomfort associated with restricted range reserves. Furthermore, it highlights the need to incorporate disutility caused by distance in the future network models used for accessing traffic at various levels of EV adoptions.

APPENDIX

Table 1: Covariates and Latent Variables

Covariates	Levels	Range Anxiety	Driving propensity
Age	Level 1	18 to 34 years	18 to 24 years
	Level 2	35 to 44 years	25 to 34 years
	Level 3	45 to 64 years	35 to 64 years
	Level 4	Above 65 years	Above 65 years
Gender	Dummy	1 = Male	1 = Male
Education	Level 1	-	Some college, Associate or Bachelor's or Master's degree
	Level 2		Doctoral degree and Professional degree (JD, MD)
Income	Level 1	Below $20,000	-
	Level 2	$20,000 to $74,999	
	Level 3	$75,000 to $149,999	
	Level 4	Above $150,000	
Car ownership	Dummy	1 = Owns a car	1 = Owns a car
Years of BEV ownership	Level 1	No BEV ownership	-
	Level 2	Less than 1 year	
	Level 3	More than 1 year	
Capacity of BEV	Level 1	Randomly assigned	-

Table 2: Indicators and Latent Variables

Indicators	# Categories	Range Anxiety	Driving Propensity
Continuous indicator			
% of income invested in a risky scheme		✓	
Range safety buffer			✓
Ordinal indicators:	***# Categories***		
Importance of fuel efficiency	4		✓
Importance of comfort	4	✓	✓
Importance of safety	4	✓	✓
Importance of performance	4		✓
Carpooling efforts	3		✓
Awareness of station location	3	✓	

Table 3: P-ICLV Variable Details

Equation	Variable	Symbol	Dimension (general)	Dimension (In this study)	Source
Structural equation	Latent variable	$\boldsymbol{z}$	$(L\times 1)$	(2×1)	-
	Co-efficient	$\boldsymbol{\alpha}$	$(L\times D)$	(2×15)	Estimated
	Covariate	$\boldsymbol{w}$	$(D\times L)$	(15×2)	Data
	Error term	$\boldsymbol{\eta}$	$(L\times 1)$	(2×1)	-
	Correlation matrix of $\boldsymbol{\eta}$	$\boldsymbol{\Gamma}$	$(L\times L)$	(2×2)	Estimated
Measurement equation (continuous indicator)	Continuous indicator	$\boldsymbol{y_c}$	$(C\times 1)$	(2×1)	Data
	Constant	$\boldsymbol{\delta_c}$	$(C\times 1)$	(2×1)	Estimated
	Co-efficient	$\boldsymbol{d_c}$	$(C\times L)$	(2×2)	Estimated
	Error term	$\boldsymbol{\xi_c}$	$(C\times 1)$	(2×1)	-
	Variance covariance matrix of $\boldsymbol{\xi_c}$	$\boldsymbol{\Sigma_c}$	$(C\times C)$	(2×2)	Estimated
Measurement equation (ordinal indicator)	Ordinal indicator	$\boldsymbol{y_o}$	$(G\times 1)$	(6×1)	Data
	Constant	$\boldsymbol{\delta_o}$	$(G\times 1)$	(6×1)	Estimated
	Co-efficient	$\boldsymbol{d_o}$	$(G\times L)$	(6×2)	Estimated
	Error term	$\boldsymbol{\xi_o}$	$(G\times 1)$	(6×1)	-
	Variance covariance matrix of $\boldsymbol{\xi_o}$	$\boldsymbol{\Sigma_o}$	$(G\times G)$	(6×6)	Estimated
	Threshold	$\boldsymbol{\psi}$			Estimated

Table 3 (Cont.): P-ICLV Variable Details

Equation	Variable	Symbol	Dimension (general)	Dimension (In this study)	Source
Measurement equation (combined form)	**Indicator**	$\boldsymbol{y}$	(M×1)	(8×1)	Data
	Constant	$\boldsymbol{\delta}$	(M×1)	(8×1)	Estimated
	Co-efficient	$\boldsymbol{d_o}$	(M×L)	(8×2)	Estimated
	Error term	$\boldsymbol{\xi}$	(M×1)	(8×1)	-
	Variance covariance matrix of $\boldsymbol{\xi}$	$\boldsymbol{\Sigma}$	(M×M)	(8×8)	Estimated
	Threshold	$\boldsymbol{\psi}$			Estimated
Choice model	**Utility**	$\boldsymbol{U_{qrk}}$	(1×1)	(1×1)	Data
	Co-efficient	$\boldsymbol{\beta}$	(B×1)	(3×1)	Estimated
	Exogenous variable	$\boldsymbol{x_{qrk}}$	(B×1)	(3×1)	Data
	Loadings	$\boldsymbol{\gamma'_{qr}\phi_{qr}} = \boldsymbol{\lambda_{qr}}$	(1×L)	(1×2)	Estimated
	Error term	$\boldsymbol{\varepsilon_{qrk}}$	(1×1)	(1×1)	-
	Variance covariance matrix of $\boldsymbol{\varepsilon}$	$\boldsymbol{\Lambda}$	(B×B)	(3×3)	Estimated

Table 4: Symbol Description

Description	Symbol	Dimension (general)	Dimension (for this study)
Individuals	q	Q	502
Routes	r	R	4
Occasions	k	K	3
Covariates	w	D	15
Indicators	y	M = C + G	8
Indicators – Continuous	y_c	C	2
Indicators – Ordinal	y_o	G	6
Exogenous variables	x	B	3

Table 5: Structural Equation Results

Latent Variable	Attribute	Attribute Level	Estimate	t-stat
Range anxiety	**Age** (Base: *less than 35 years and 65+*)	Between 35 & 44 years	1.144	2.835
		Between 45 & 64 years	1.131	2.920
	Gender	Male	0.328	2.584
	Income (Base: *below $20,000*)	Between $20,000–75,000	1.127	2.902
		Between $75,000–150,000	1.329	2.950
		Above $150,000	1.114	2.970
	BEV ownership (Base: *does not owns BEV*)	Owns BEV	4.397	2.937
	Car-ownership (Base: *owns at the least one car*)	No car-ownership	0.261	1.794
Driving Propensity	**Age** (Base : *between 25 & 34 years*)	Between 18 & 24 years	0.054	3.332
		Between 35 & 64 years	0.315	17.106
		greater than 64 years	0.484	15.791
	Gender	Male	0.135	9.723
	Education status (Base: *doctoral degree and other professional degree [PhD, JD, MD]*)	High school, Some college, Associate or Bachelor's degree or Master's degree	0.060	2.943
Correlation co-efficient between range anxiety and driving propensity latent variable			-0.388	-2.424

Table 6: Measurement Equation Results

Indicator type	Indicator	Indicator specific constant	Range anxiety		Driving propensity	
			Estimate	t-stat	Estimate	t-stat
Continuous variables	% of income invested in a risky scheme	0.5162	-0.051	-1.977	-----	-----
	Min. range safety buffer (in miles)	0.3215	-----	-----	-0.071	-2.262
Ordinal variables	Importance of fuel efficiency	1.3335	-----	-----	0.129	4.025
	Importance of comfort	1.8846	-0.029	-2.428	1.170	14.874
	Importance of safety	1.9660	-0.078	-2.906	0.673	13.780
	Importance of performance	0.8232	-----	-----	0.811	15.375
	Carpooling efforts	0.1376	-----	-----	-0.175	-5.031
	Awareness of station location	1.5904	-0.3543	-2.636	-----	-----

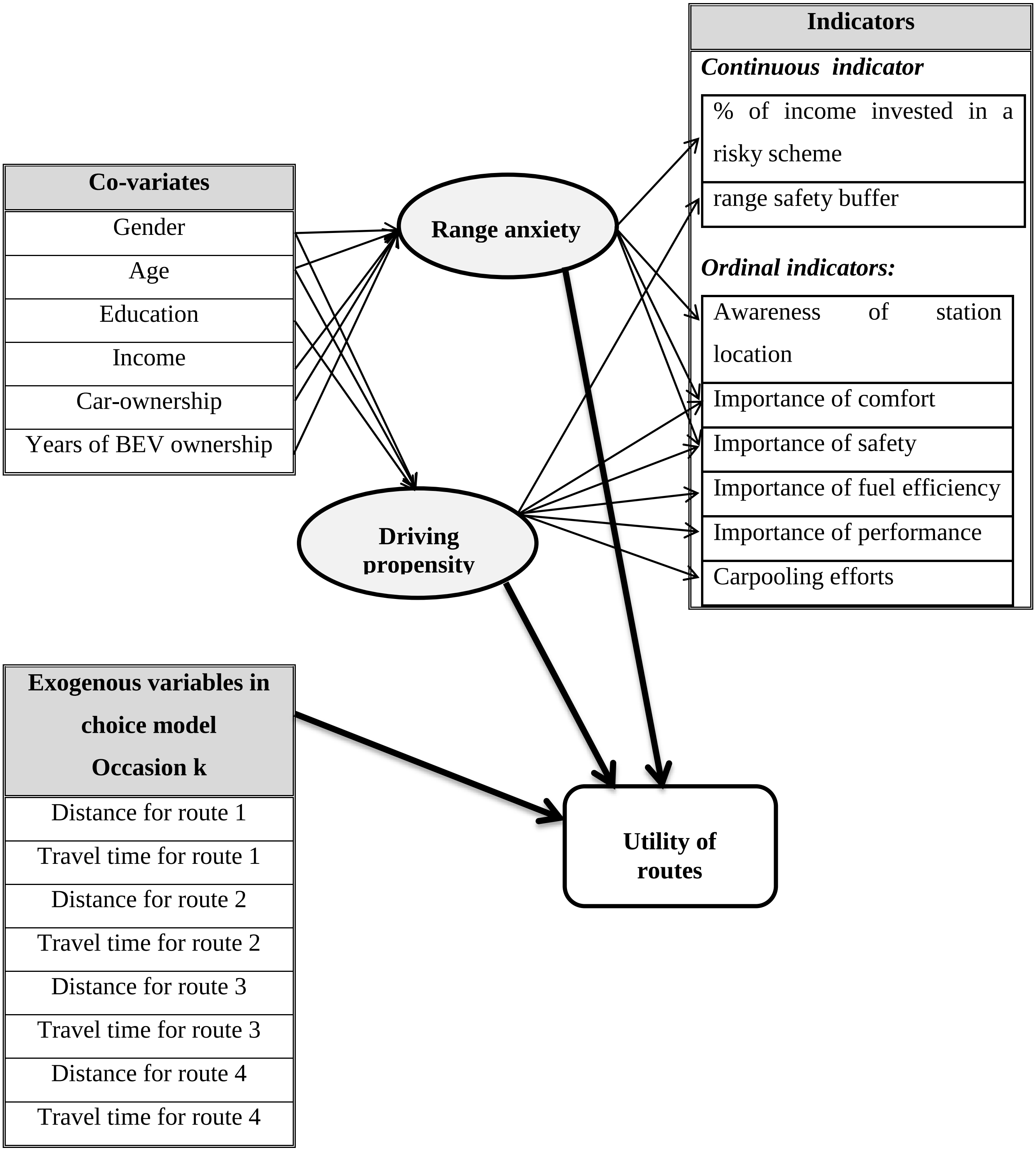
Table 7: Choice Model Results

Variables	Estimate	t-stat
Distance	-7.774	-60.583
Travel time (TT)	-2.032	-46.099
Range available	0.359	40.854
Range anxiety*Distance	-0.555	-2.866
Driving propensity*Distance	-2.433	-9.611
Range anxiety*Travel time	-0.231	-2.891
Driving propensity*Travel time	-0.873	-12.580

Table 8: Variance and Threshold Values of Indicators

Indicator type	Indicator		Variance/Threshold	
			Estimate	t-stat
Continuous variables	% of income invested in a risky scheme	$\boldsymbol{\Sigma}_1$	1.055	27.028
	Min. range safety buffer (in miles)	$\boldsymbol{\Sigma}_2$	1.000 (fixed)	--------
Ordinal variables	Importance of fuel efficiency *(Scale of 4)*	ψ_2	0.421	30.575
		ψ_3	1.403	80.092
	Importance of comfort *(Scale of 4)*	ψ_2	1.702	23.773
		ψ_3	3.673	25.842
	Importance of safety *(Scale of 4)*	ψ_2	0.982	28.697
		ψ_3	2.291	39.653
	Importance of performance *(Scale of 4)*	ψ_2	1.171	36.894
		ψ_3	2.474	39.332
	Carpooling efforts *(Scale of 3)*	ψ_1	0.854	72.854
	Awareness of station location *(Scale of 3)*	ψ_1	1.121	23.941

Figure 1: Conceptual route choice diagram.



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